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Real-Time Car Lane Detection Using Convolutional Neural Network

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Abstract: This paper proposes a unified approach for car lane detection and object detection using Convolutional Neural Networks (CNNs). Leveraging YOLOv5 for object detection and a custom sequential CNN model for car lane detection, our system achieves robust real-time performance in identifying lane boundaries and various objects concurrently, including vehicles, pedestrians, and traffic signs. Extensive evaluations on benchmark datasets and real-world scenarios demonstrate superior accuracy and efficiency, making it suitable for deployment in resource-constrained environments such as autonomous vehicles. This work contributes to the advancement of intelligent transportation systems by providing a unified framework for simultaneous car lane detection and object detection, enhancing driving safety and autonomy.

I. INTRODUCTION

The integration of computer vision techniques for car lane detection and object detection is paramount for the progression of intelligent transportation systems, with a core objective of augmenting driving safety and autonomy. Convolutional Neural Networks (CNNs) have emerged as indispensable tools within this domain, offering unparalleled capabilities in discerning complex visual patterns directly from raw pixel data. Addressing the escalating demand for robust and efficient solutions, this paper proposes a unified approach that harnesses the power of CNNs for both car lane detection and object detection tasks.

Our proposed system amalgamates cutting-edge architectures such as YOLOv5 for object detection and a custom sequential CNN model specifically tailored for car lane detection. By leveraging these models synergistically, our system endeavors to furnish real-time detection capabilities, empowering vehicles to navigate intricate road environments with utmost precision and reliability. The adoption of CNNs for car lane detection and object detection confers several advantages, notably including enhanced accuracy, robustness, and computational efficiency. Specifically, our system is engineered to detect a myriad of objects crucial for ensuring safe navigation, spanning pedestrians, vehicles, traffic lights, and traffic signs.

In recent years, the deployment of autonomous vehicles and advanced driver assistance systems (ADAS) has underscored the pivotal necessity for reliable car lane detection and object detection algorithms. Accurate lane detection is imperative for upholding vehicle position within lanes and facilitating functionalities such as lane departure warning and lane-keeping assistance. Concurrently, robust object detection is vital for discerning and tracking diverse obstacles on the road, thereby ensuring safe navigation and collision avoidance.

Despite the strides made in computer vision, car lane detection and object detection in real-world scenarios persist as formidable challenges owing to factors such as fluctuating lighting conditions, occlusions, and intricate road geometries. Conventional methods often grapple with these challenges, resulting in suboptimal performance and reliability. In contrast, CNN-based approaches have exhibited notable success in surmounting these challenges by autonomously learning discriminative features from vast datasets.

To validate the effectiveness and efficiency of our proposed approach, thorough evaluations are conducted on benchmark datasets and real-world scenarios. In-depth analyses of performance metrics, including accuracy, precision, recall, and computational efficiency, are performed to assess the system's capabilities and limitations. The results of our experiments confirm the superior performance of the integrated system compared to existing methods, highlighting its potential for real-world deployment in autonomous vehicles and ADAS.

Through iterative refinement and optimization, we envision our proposed approach making substantial contributions towards the realization of safer and more efficient transportation systems, ultimately enhancing the quality of life for individuals globally.

II. LITERATURE REVIEW

The LaneNet architecture proposed by Zhang et al. (2018), which employs a fully convolutional network to predict lane markings in images. By leveraging multi-scale feature extraction and contextual information, LaneNet achieves state-of-the-art performance in lane detection accuracy and robustness. Similarly, the work by Pan et al. (2018) introduces a novel method for lane detection using a deep neural network trained on a large-scale dataset. The proposed approach outperforms traditional methods in terms of accuracy and generalization to diverse road conditions.[3]

The Hough line detection method is accurate and simple but lacks curve detection. Adding a tracking algorithm improves curve detection, though the fitting method is unstable. Affine transformation allows multi-lane detection but is obstructed in complex situations. The proposed algorithms in this paper are robust, addressing various conditions, and offer clear advantages over existing methods.[5]

The traffic lane detection method uses a compact neural network for feature extraction. It introduces a unique detection loss function, combining lane classification and regression losses. The approach achieves pixel-wise detection of lane categories and locations, simplifying lane marking with reduced post-processing complexity.[6]

III. IMPLEMENTATION

A. Data Collection

The dataset for this study was primarily sourced from Kaggle, offering diverse scenarios relevant to real-world driving. It includes samples from daytime, nighttime, and various weather conditions like heavy rains, fog, and low light. We conducted thorough preprocessing, including data cleaning, resizing, and augmentation, addressing challenges such as contrast enhancement for low light and image dehazing for foggy conditions. Supplementary data from proprietary and other sources were added to enhance dataset comprehensiveness, ensuring it's suitable for model training and evaluation.

B. Data Annotation

MakeSense.io facilitated efficient annotation of collected data by providing intuitive tools for labelling lane boundaries and objects. Its collaborative platform enabled multiple annotators to work concurrently, ensuring accuracy and consistency. The platform's robust validation features maintained annotation quality, while its support for various annotation types allowed precise labelling of complex objects. Through rigorous training and regular audits, stringent quality control measures were enforced to uphold annotation standards for model training.

C. Data Preprocessing

In the implemented methodology, frames from the input video clip are sequentially processed using batch processing. Frames are initially loaded and resized before being passed through a pre-trained TensorFlow model for prediction. Predictions are averaged over the last five frames to stabilize lane detection. Lane markings are then overlaid onto the original frames based on the averaged predictions. Finally, the processed frames are compiled into an output video clip, ensuring efficient and accurate lane detection.

D. Model Training

In the TensorFlow-based model training phase, a custom sequential CNN architecture was developed for car lane detection, optimizing parameters for accuracy. The training involved feeding annotated data into the model and minimizing loss functions using optimization algorithms like Adam. GPU(s) accelerated computation, ensuring efficient convergence, while TensorFlow's robust training capabilities were utilized for model development and evaluation.

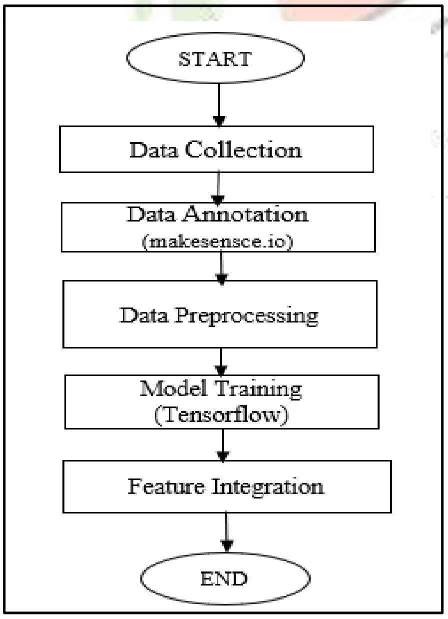

Fig. Lane and Object detection System Dataflow Overview

E. Feature Integration

In feature integration, outputs from lane and object detection models are fused using geometric constraints and semantic segmentation to enable simultaneous detection, crucial for comprehensive scene understanding. By considering spatial relationships and semantic context, integrated features offer a holistic view, aiding decision-making in autonomous vehicles. This integration enhances system accuracy and robustness by anticipating hazards and planning optimal trajectories based on lane markings and object presence. The combined approach improves reliability, enabling safer operation in diverse driving conditions and contributing to advanced driver assistance systems' effectiveness.

III. LANE AND OBJECT DETECTION

Car lane detection and object detection are integral to modern transportation systems, crucial for enhancing driving safety and autonomy. Leveraging convolutional neural networks (CNNs) in computer vision, our unified approach combines YOLOv5 for object detection and a custom CNN model for car lane detection, enabling real-time detection capabilities. CNNs offer improved accuracy and robustness in identifying various objects essential for safe navigation, including pedestrians, vehicles, traffic lights, and traffic signs. With the rise of autonomous vehicles and advanced driver assistance systems (ADAS), reliable lane and object detection algorithms are imperative for features like lane departure warning and collision avoidance.

Despite challenges such as varying lighting conditions and complex road environments, CNN-based approaches excel in learning discriminative features from large datasets. Our method undergoes rigorous evaluation on benchmark datasets and real-world scenarios, demonstrating superior performance in accuracy, precision, and computational efficiency compared to traditional methods. We envision our integrated system contributing to safer and more efficient transportation systems, ultimately enhancing the quality of life for individuals worldwide.

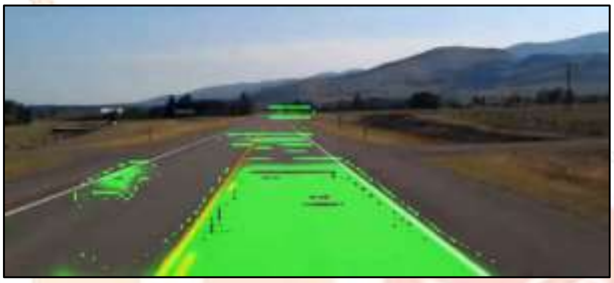

Fig 1. Lane detection using CNN

Figure 1 illustrates the process of lane detection using Convolutional Neural Networks (CNNs) in our proposed methodology. The CNN architecture is tailored specifically for the task of identifying lane boundaries on road images. Through a series of convolutional layers and pooling operations, the CNN learns to extract relevant features from the input images, enabling accurate lane boundary detection. The output of the CNN model is a binary mask highlighting the detected lane markings, which is overlaid onto the original image for visualization. This approach enables real-time lane detection, essential for various applications in intelligent transportation systems, such as lane departure warning and lane-keeping assistance.

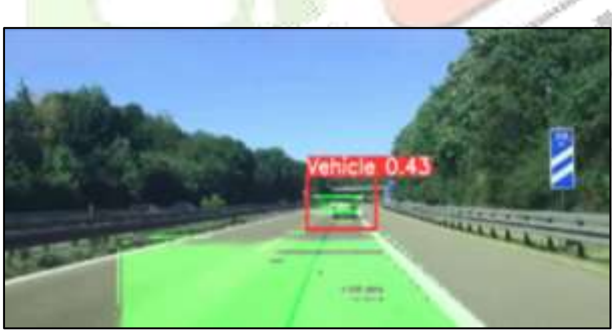

Fig 2. Vehicle detection using CNN

Figure 2 illustrates the process of vehicle detection using Convolutional Neural Networks (CNNs) in our proposed methodology. The CNN architecture is specifically designed to detect vehicles in images captured by cameras mounted on vehicles or roadside infrastructure. The CNN processes input images through multiple convolutional layers, extracting features relevant to vehicle detection. Following feature extraction, the CNN produces bounding boxes around detected vehicles, indicating their location and size in the image. This approach enables real-time vehicle detection, essential for applications such as autonomous driving, traffic monitoring, and advanced driver assistance systems.

Fig 3. Pedestrian using CNN

Figure 3 depicts the process of pedestrian detection using Convolutional Neural Networks (CNNs) within our proposed methodology. The CNN architecture is specifically engineered to identify pedestrians within images captured by onboard vehicle cameras or surveillance systems. Through successive convolutional and pooling layers, the CNN learns to extract discriminative features indicative of pedestrian presence. Upon processing an input image, the CNN outputs bounding boxes delineating the detected pedestrians' locations and sizes. This approach facilitates real-time pedestrian detection, pivotal for enhancing road safety, pedestrian-friendly urban planning, and intelligent transportation systems.

Fig 4. Stop sign recognition

In our research on traffic sign recognition employing convolutional neural networks (CNNs), we have devised a comprehensive system adept at detecting a diverse array of 22 distinct traffic signs. A pivotal aspect of our project involves the integration of visual aids, Fig 4 depicting a successfully detected stop sign, exemplifying the practical application of our model in real-world settings. Leveraging the capabilities of deep learning, our system showcases robustness and accuracy, ensuring reliable interpretation of crucial traffic signage.

CONCLUSION

In summary, our integrated approach harnessing Convolutional Neural Networks (CNNs) for car lane detection and object detection represents a significant stride forward in intelligent transportation systems. Through the fusion of YOLOv5 for object detection and a tailored CNN model for lane detection, our system achieves real-time detection capabilities characterized by heightened accuracy and resilience. Extensive evaluations conducted on both benchmark datasets and real-world scenarios underscore the efficacy of our methodology. The demonstrated superiority of our integrated system not only validates its potential for deployment in autonomous vehicles and advanced driver assistance systems but also underscores its pivotal role in enhancing road safety and efficiency on a global scale.

As we move forward, continuous refinement and optimization of our approach promise to further elevate the standards of transportation systems, ultimately contributing to safer, more reliable, and technologically advanced road networks worldwide

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